# Mapping the effects of drought on child stunting

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**As climate change continues, it is expected to have increasingly adverse impacts on child nutrition outcomes, and these impacts will be moderated by a variety of governmental, economic, infrastructural, and environmental factors. To date, attempts to map the vulnerability of food systems to climate change and drought have focused on mapping these factors but have not incorporated observations of historic climate shocks and nutrition outcomes. We significantly improve on these approaches by using over 580,000 observations of children from 53 countries to examine how precipitation extremes since 1990 have affected nutrition outcomes. We show that precipitation extremes and drought in particular are associated with worse child nutrition. We further show that the effects of drought on child undernutrition are mitigated or amplified by a variety of factors that affect both the adaptive capacity and sensitivity of local food systems with respect to shocks. Finally, we estimate a model drawing on historical observations of drought, geographic conditions, and nutrition outcomes to make a global map of where child stunting would be expected to increase under drought based on current conditions. As climate change makes drought more commonplace and more severe, these results will aid policymakers by highlighting which areas are most vulnerable as well as which factors contribute the most to creating resilient food systems.**

child stunting | undernutrition | drought | vulnerability mapping

Currently, 1 in 9 people around the world are undernourished and nearly half of the deaths in children under 5 y of age are caused by poor nutrition (1). One of the consequences of poor child nutrition is stunting, which affects more than 1 in 3 children in many developing countries (2). Stunting can lead to a higher risk of mortality as a child (3), as well as reduced physical, cognitive, and educational attainments and lifelong health problems from reduced immunity and increased disease susceptibility (4). The effects of stunting on a population are long term: the children of parents who experienced early childhood stunting are in turn at higher risk for lower developmental levels (5). Due to decreased earnings and economic output, child stunting can hamper long-term economic growth for generations (6). Thus, ameliorating child stunting is a critical component of sustainable development (7). While rates of stunting have been in decline globally over the past few decades, hotspots of stunting remain in Africa and South Asia (8). Furthermore, because stunting has been shown to be very sensitive to climate shocks (9, 10), climate change could stall or even reverse current gains (1).

Climate change is now widely acknowledged to be a threat to food security and nutrition globally. Rising temperatures due to increased greenhouse gas emissions will change patterns of precipitation and temperature around the world, in turn affecting food production and infrastructure critical to food distribution (11). All of these impacts will affect child nutrition outcomes, which is why both the World Health Organization (WHO) and the Intergovernmental Panel on Climate Change (IPCC) have identified undernutrition as a major expected health impact of climate change (12, 13). Most directly, climate change will affect crop production and therefore food availability (14). In many parts of the world, precipitation shortfalls will become more frequent and severe, while rising temperatures will increase rates of evapotranspiration and cause drought conditions even in areas with sufficient rainfall (15), ultimately leading to lower crop yields and worsened food security and nutrition for vulnerable populations (16).

While climate change is recognized as a major threat to child nutrition, insufficient research has been conducted associating the effects of precipitation and temperature shocks with worsened nutrition outcomes. A 2015 review paper documented 15 studies that used regression techniques to find an association between meteorological or agricultural variables and child nutrition outcomes, and the paper ultimately characterized the current evidence as "scattered and limited" (17). In this literature review, only 2 studies were multinational, and the largest sample size was about 19,000 children. Since 2015, more work has been done to confirm associations between low rainfall and rates of stunting (18), as well as to examine factors that can mitigate the effects of rainfall anomalies on child nutrition (9). Nevertheless, there is still a significant dearth of research that draws on empirical observations of child nutrition and climate impacts, especially using large pools of data with the spatiotemporal variability that is needed to model outcomes across geographic contexts.

Because the primary impact of climate change will be on food production, much of the research on the expected impacts of climate change on food security focuses on agricultural yields. While farmers in general and subsistence farmers in particular will be quite affected by climate change, whether or not its impacts lead to increased child undernutrition depends on a variety of factors that ultimately affect food access, such as equitable food distribution, government safety nets, and resilient trade systems (19). As recent droughts in Southern and Eastern Africa

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## Significance

**We use geolocated child nutrition data from 53 developing countries to show that minor to severe droughts as well as severe periods of extreme rainfall are related to child stunting. We then explore how various geographic factors mitigate or amplify the effect of drought on child heights. Finally, we combine global data on these factors to map where child stunting is currently vulnerable to drought, finding that arid low-income countries with poor governance and political instability are where drought could have the largest effect on child stunting.**

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demonstrate (20, 21), there can be significant spatial heterogeneity in which populations are most affected and vulnerability is influenced by a variety of political, social, economic, agricultural, and environmental factors.

Focusing on these factors influencing vulnerability, some studies have been conducted at global and continental scales to create indicators that highlight hotspots of risk. Such studies include efforts to map drought risk (22), the risk of climate change impacts on food security (23–25), as well as mapping climate risks for security more broadly (26). While these studies recognize the importance of locating the populations most vulnerable to climate impacts, they often rely on highly aggregated data and make no predictions about actual impacts, but simply highlight areas of general risk or severity. Furthermore, because these studies lack an empirical basis to estimate how different factors affect climate change vulnerability, they often weigh diverse variables equally when combining them into an indicator—for example, deriving subindicators and taking the average (22, 24). In this study, we improve upon these methods by using an econometric approach to map the anticipated effects of drought on child stunting globally.

To map where child nutrition is vulnerable to precipitation shocks and explore which factors moderate vulnerability, we combine nutrition data from Demographic and Health Surveys (DHS) with climatological data, as well as a variety of global datasets on factors influencing both the sensitivity of local food systems to drought as well as local adaptive capacity from sources such as the World Bank, the Food and Agriculture Organization of the United Nations, and NASA, as well as datasets published in scientific journals. Deriving the Standardized Precipitation–Evapotranspiration Index (SPEI) from the climatological data, we show how precipitation anomalies are related to increased child stunting (Fig. 1). We then model how various factors have historically either mitigated or amplified the effect of drought on child stunting (Fig. 2) and combine global data on these factors to estimate current

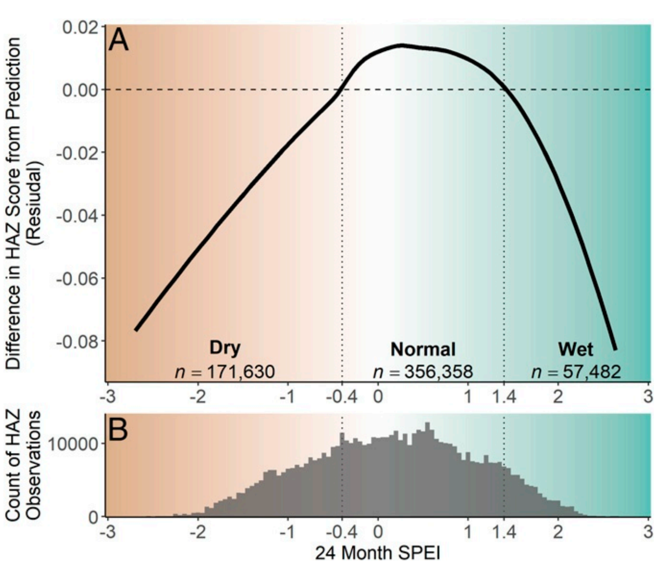


**Fig. 1.** (*A*) Relationship between the 24-mo SPEI and residual HAZ scores. During periods of normal rainfall, children were typically taller than household and individual factors would otherwise predict (residual $>$ 0). Conversely, during periods of minor to severe drought and during periods of severe wetness, children were typically shorter (residual $<$ 0). This nonparametric analysis was used the discretize the 24-mo SPEI variable into drought and normal periods and to exclude extremely wet periods, based on the cutoffs at −0.4 and 1.4. (*B*) Histogram of child nutrition observations at various SPEI levels.

drought vulnerability (Fig. 3). Finally, for 2 areas that have recently experienced drought, we make a qualitative comparison of our model's predictions of increases in stunting with observed increases in food insecurity during those droughts (*SI Appendix*, Fig. S4).

## Results

**Rainfall Anomalies and Height-for-Age Z Scores.** We began by determining the time window at which SPEI values best predict child heights and found that the 24-mo SPEI performs better than SPEI values calculated for other time windows, including each child's age (*SI Appendix*, Tables S1 and S2). We then explored the effects of rainfall anomalies on observed child Height-for-Age Z scores (or HAZ scores), a common indicator of child stunting (1). We used a Locally Estimated Scatterplot Smoothing (LOESS) regression because it can model the anticipated nonlinear relationship between anomalies and child stunting. After controlling for the effects of individual, household, annual, and national factors, there was a clear relationship between the 24-mo SPEI and child HAZ scores. The fitted curve shows that children have the highest HAZ scores when rainfall is between the long-term norm (SPEI = 0) and a mildly wet period (SPEI = 1). As rainfall levels increase relative to long-term norms, HAZ scores decline slightly, and then as the SPEI increases beyond 1.4, child HAZ scores decline sharply. Child HAZ scores decrease monotonically with rainfall deficits at all levels. Even when the previous 24 mo were only slightly drier than the long-term norm, HAZ scores were slightly worse, and SPEI scores less than −0.4 were associated with children shorter than other relevant factors would otherwise predict.

**Modeling Combined Effects of Geographic Factors.** Based on the results of the LOESS model, we identified the points at which low and high rainfall levels are associated with worsened child nutrition outcomes and focused the rest of the analysis on comparing children observed during droughts (SPEI $<$ −0.4) with those observed during normal rainfall periods (−0.4 $<$ SPEI $<$ 1.4). This was because higher-than-average rainfall was not related to lower HAZ scores unless it was extreme, while lower-then-average rainfall was related to lower HAZ scores even at minor levels, yielding a large number of children in a wide variety of geographical contexts observed during drought but fewer children observed during excessively wet periods. Furthermore, the effects of drought on food production occur at the location of the drought, while the effects of excess rainfall, such as flooding and landslides, can be caused by rainfall far from the location of a child nutrition observation.

To determine how various geographic factors moderate this relationship between drought and stunting, we modeled a variety of geographic factors in interaction with whether a child was observed during drought conditions, and we show that many variables influence whether or not a drought will be associated with decreases in HAZ scores (Fig. 2). Factors having a large effect on mitigating the impacts of drought on HAZ scores include the nutritional diversity of local agricultural systems, effective governments, greater imports and staple crop production, a higher percentage of irrigated agriculture, political stability, and greater mean annual precipitation. Factors that exacerbate the effects of drought include higher population densities, higher average monthly maximum temperature, a higher percentage of bare land cover, and greater topographic ruggedness. The Normalized Difference Vegetation Index, Human Development Index, and gross domestic product dropped out of the model (*SI Appendix*, Table S3).

We modeled the impact of drought as being moderated by only geographic factors. Because of this, we were able to then predict changes in HAZ scores under drought globally, including in

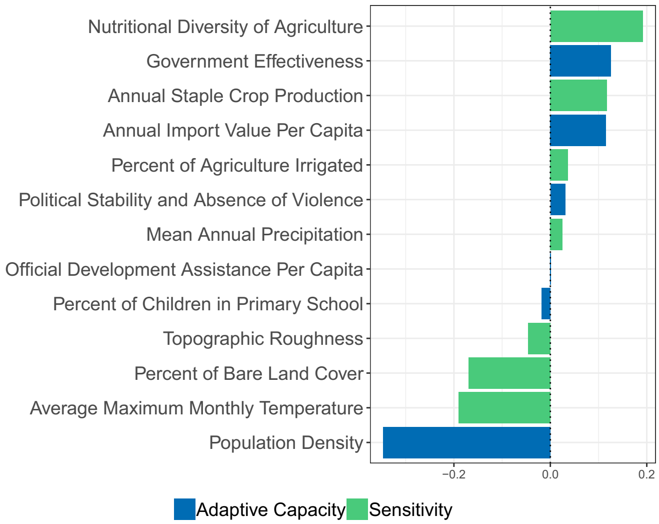


**Fig. 2.** Coefficient estimates of geographic variables moderating the effects of drought on child HAZ scores. Positive coefficients mitigate the effects of drought, while negative coefficients exacerbate the effects of drought. Some variables were log-transformed, and then all variables were scaled from 0 to 1. Variables are color-coded according to whether they characterize a system's sensitivity to shocks (green) or adaptive capacity (blue).

countries that did not have DHS data, based on geographic data for as close to the year 2020 as possible. Thus, we weighed global data on factors that moderate the effects of drought according to the coefficients estimated from our model to predict changes in HAZ scores under drought (Fig. 3). This map showed that the most drought vulnerable children are in arid areas with weak governments and little international trade, such as Chad, Sudan, Eritrea, South Sudan, Somalia, and Yemen. In addition to these hotspots of drought vulnerability, other areas with some vulnerability included other countries throughout Africa, central Asia, and the Middle East, as well as Papua New Guinea, North Korea, and Haiti. Comparing our model's predictions with observed changes in food insecurity during recent droughts in southern and eastern Africa shows that our model performs quite well (*SI Appendix*, Fig. S4).

## Discussion

A significant advantage of this study was using a very large dataset, which allowed us to draw on observations of child nutrition outcomes during droughts across a range of economic, political, and agroenvironmental conditions. We were thus able infer how these conditions moderate the relationship between drought periods and child HAZ scores. We found that precipitation deviations from long-term norms such as minor to severe droughts or severely wet periods were associated with worse child nutrition, as measured by child HAZ scores. Using geographic data associated with the time and location of each child nutrition observation, we modeled how a variety of geospatial factors amplify or mitigate the effects of drought. Finally, we used this model to predict globally where current geographic contexts could contribute to worsened child nutrition outcomes during the event of a drought, based on how those factors have historically moderated the relationship between drought and HAZ scores.

In assessing the relationship between rainfall anomalies and child undernutrition, previous studies have taken varied approaches, with some measuring lifetime growing season precipitation levels (9, 10) and others looking at rainfall in recent seasons (27). Thus, we compared precipitation deviations from long-term norms at multiple timescales for both growing-season precipitation and full-year precipitation, and we found that the full-year 24-mo SPEI performed the best in modeling child HAZ scores. Although a child's HAZ score is affected by chronic, long-term undernutrition, the 24-mo SPEI score performed better than indicators over other time frames, including the SPEI for the child's lifetime. This may be due to children experiencing rapid growth when they receive adequate nutrition following a period of poor nutrition, a phenomenon known as compensatory growth or catch-up growth (28, 29).

We found that a variety of factors improve child nutrition outcomes under drought. While many of these factors have been previously associated with positive nutrition outcomes, including agricultural and dietary diversity (30), crop production (31), and trade (32), relatively little research has been conducted exploring their role in mitigating the effects of drought on child nutrition. Our results indicate that, to build climate-resilient nutrition systems, policymakers at the national level should focus on effective governance and trade, while local interventions should focus on increasing the nutritional diversity of agricultural systems as

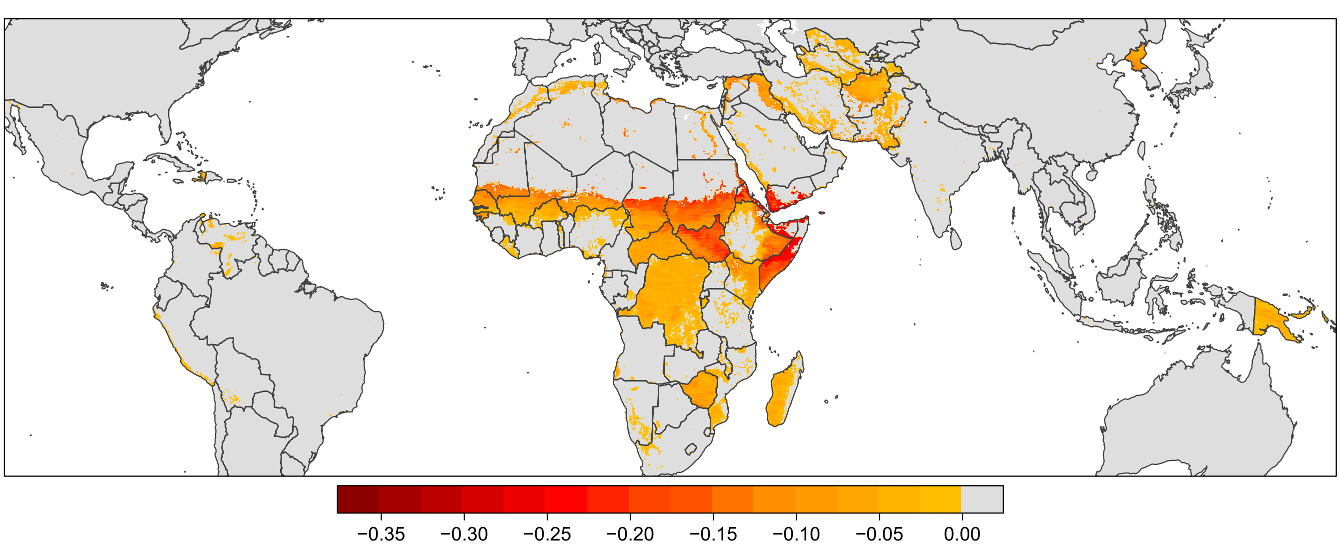


**Fig. 3.** Expected decrease in mean child HAZ scores during drought conditions.

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well as restoring degraded and bare land. Our results further indicate that increasing crop yields in vulnerable countries can improve drought resilience, while climate change may exacerbate vulnerability by raising temperatures and lowering rainfall averages.

Beyond just showing which geographic factors amplify or mitigate vulnerability, this study also mapped the expected impact of precipitation extremes on child HAZ scores. This improves upon previous mapping efforts that have similarly focused on geographic variables that influence vulnerability (33) but have relied on index-based methods that take an a priori approach to combining these variables (22–26). By using a more empirical approach, we are able to map vulnerability by weighing various geographic factors according to how much they have historically been observed to moderate the relationship between drought and lower HAZ scores.

There are several assumptions and simplifications built into the model. For the purposes of this paper, rainfall deficits across a wide range of levels were combined into the category of drought. Most of these droughts were moderate and not uncommon, with an SPEI between $-0.4$ and $-1.5$, and thus this map does not show the anticipated effects of severe droughts that could become more common under climate change. Many areas besides those highlighted in this map would likely see nutritional decreases under severe droughts, and areas shown in this analysis to be vulnerable to moderate drought, like Somalia and the Sahel, would likely see extreme increases in stunting and even famine under severe droughts. Furthermore, this analysis relies on some geographic data that is only available at the national level, which may obscure significant subnational vulnerability, for example, in countries with pockets of instability, such as Nigeria (34). Thus, our map is less useful for local and national policymakers who already have substantial understanding of the spatial distribution of drought vulnerability in the countries where they work. Rather, our map is most applicable for nongovernmental organizations, foundations, and multinational organizations seeking to target vulnerable populations and prioritize aid at global and continental scales.

While many of the areas identified by our model as vulnerable to drought have been the location of previous studies associating precipitation and undernutrition (10, 35–39), there were some areas where previous literature had found associations between precipitation shortfalls and worsened nutrition outcomes and where our model predicted little vulnerability, such as Nepal (9, 40), Rwanda (41), Indonesia (42), Mexico (27), and India (43). This may be due in part due to the aforementioned issue of our model relying on national indicators for countries with substantial within-country heterogeneity, particularly for large middle-income countries such as Indonesia, Mexico, and India. This suggests that our model might be best taken as a conservative estimate of where drought-induced undernutrition is likely to occur but not a prediction of where it will not occur, given that poorer and more rural subpopulations in many countries may be more vulnerable to climate change than national statistics or historic population-level shifts in HAZ scores would indicate (44). However, another potential reason for our model disagreeing with previous studies is that they may have taken place several years ago using datasets that were even older, and increases in trade, wealth, and stability over the previous few decades have led to decreases in drought vulnerability. Indeed, using our model to predict vulnerability based on geographic data from the years 2000 and 1990 (*SI Appendix*, Figs. S1 and S2) shows that droughts in those years would have led to greater decreases in mean HAZ scores in many places than a drought would today, and that areas modeled as drought-resilient in 2020, such as India, were previously more drought vulnerable.

Data on HAZ scores with high temporal frequency are unavailable at the global scale to validate our model, so we used reports on IPCC phases from the Famine Early Warning Systems Network (FEWS NET) in food insecure regions to perform a qualitative ground-truthing of our model's predictions. Indeed, we found that our model broadly agrees with FEWS NET's reports of where food security worsened after the onset of recent droughts in Southern Africa and East Africa (*SI Appendix*, Fig. S4). This suggests that our model is useful as a framework for using empirical methods to estimate vulnerability spatially and also suggests that there is validity to the geographic factors that our model identified as amplifying or moderating the effects of drought.

Overall, our findings have significant implications for policymakers, foundations, and multinational organizations interested in targets such as Sustainable Development Goal (SDG) 2 of achieving zero hunger, as well as SDG 13 of taking action to combat climate change impacts. First, we show that precipitation extremes are associated with worse child nutrition outcomes throughout much of the developing world. This supports the assertions of the WHO and IPCC that climate change, which will make extremes both more common and more severe, is a significant threat to adequate nutrition for much of the world (12, 13). Secondly, we highlight the factors that can increase both vulnerability and resilience to droughts. Nutritionally diverse agricultural systems and effective governance, staple crop production, and international trade were found to have a large impact on drought resilience, and thus investing in these aspects of food systems would be expected to pay large dividends in increasing climate resilience. Finally, we mapped areas where droughts would be expected to lead to increased rates of undernutrition, with the expectation that such maps would assist global policymakers in targeting aid to improve climate resilience for the world's most vulnerable populations.

## Data Used

**Nutrition Data.** We use geolocated child nutrition data from the DHS program in combination with a variety of geographic datasets. Our dataset consists of 584,662 children from 127 surveys conducted in 53 countries over 26 y, from 1990 to 2016 (*SI Appendix*, Fig. S3). To focus the analysis on children in households with livelihoods that are at least partially agricultural, we excluded children who were from DHS sites in areas with greater than 95% of nearby land cover classified as bare ground (45) or with greater than 20% of nearby land cover classified as built up (46). This excluded 1.1% of the children and consisted mostly of children from extremely arid places, like the central Sahara desert, or highly urban places. While DHS surveys are often conducted periodically within a given country, they do not intentionally revisit the same communities, so the surveys are not longitudinal and every child is observed only once.

For children under 5 y of age, environmental factors explain more variation in height than ethnic differences (47). Thus, child heights are a widely accepted indicator of child nutrition. For this analysis, our outcome variable is the HAZ for children under 5 y old, which is a standardized measure of child heights and a common indicator of stunting. This indicator compares a child's height to the distribution of heights of healthy children of the same age and gender and assigns a Z score. The percent of children with a Z score less than $-2$ in a given population is the rate of stunting for that population (48). Thus, while exact changes in the rate of stunting in a population cannot be derived from changes in HAZ scores alone, decreases in mean HAZ scores will lead to increases in stunting.

To better estimate the impact of rainfall anomalies on an individual child's HAZ score, it is important to control for individual- and household-level variables that can also affect child health outcomes, such as the child's birth order or household wealth. The DHS includes many such variables, although few are collected in all surveys. We identified 10 variables that were available in 127 DHS surveys and that robustly predicted child HAZ scores (*SI Appendix*, Tables S4 and S5). While not all of the surveys in our dataset asked how long the households had been residing at the site or whether they were visitors, for those that did, if the households were visitors or had been residing at the site for less than 3 y, we excluded them from the dataset.

**Data on Shocks.** As an indicator of precipitation extremes, we used the SPEI, a measure of how recent hydrological conditions over a given time frame vary with respect to long-term norms, taking both rainfall and evapotranspiration into account (49). By accounting for water lost to evapotranspiration, the SPEI can more accurately indicate the overall water availability and agricultural stress at a location. Furthermore, because this metric is based on long-term norms for a given location, it characterizes precipitation extremes in a way that is comparable between locations. We used reanalysis datasets of precipitation (50) and temperature (51) to calculate the SPEI and derived potential evapotranspiration (PET) using the Hargreaves method. Finally, we calculated rainfall levels during the growing season at each site (52) and compared models with SPEI scored derived from full-year and growing season-only precipitation at 12-, 24-, and 36-mo intervals, as well as for the duration each child's lifetime, including time in utero.

**Data on Factors Influencing Vulnerability.** We modeled how various factors mitigate or amplify the impacts of rainfall shocks on child HAZ scores. In our model, we draw on previous frameworks that characterize vulnerability in terms of sensitivity, adaptive capacity, and hazard (24). We thus include geographic variables that describe the sensitivity and adaptive capacity of a system vis-à-vis a hazard (i.e., drought). Variables characterizing the sensitivity of the food system to shocks include primarily agroecological variables, while variables characterizing the adaptive capacity of households facing drought include primarily economic, demographic, and geopolitical variables (*SI Appendix*, Table S6). For each of these geographic variables, we fit the model using data for the year of the DHS survey, or the nearest available year, and for the final map (Fig. 3), we use data for the closest available year to 2020.

## Methods

**Rainfall Anomalies and Undernutrition.** To control for individual, household, and national factors in our LOESS model of rainfall anomalies and undernutrition, we first modeled HAZ scores as a function of 10 individual and household covariates, with varying intercepts at the country and DHS survey level. We then predicted the residuals from this regression as a function of the 24-mo SPEI using a LOESS model with a $2^{nd}$ degree polynomial and tricubic weighting on a local window size of 75% of the data.

**Factors Moderating the Effects of Rainfall Anomalies.** Based on the results of the LOESS model, we identified the points at which low and high rainfall levels are associated with worsened child nutrition outcomes and focused the rest of the analysis on children observed during droughts and during normal rainfall periods. We thus excluded all observations with extremely high SPEI values (SPEI $> 1.4$) and created a categorical variable for the remaining observations indicating whether the child was observed during a drought period (SPEI $< -0.4$) or a normal period ($-0.4 <$ SPEI $< 1.4$).

We modeled child HAZ scores as a function of household, individual, and geographic factors, and we modeled each geographic factor interacting with the categorical variable for whether the child was observed during a drought. Formally, we ran the following linear regression:

$$y_i = \beta_0 + \beta X_i + \gamma G_{j(i)} D_{j(i)} + \epsilon_i, \quad [1]$$

where $i$ is the index for each individual child and $j$ is the index for the DHS site, $y_i$ is a child's HAZ score, $\beta$ is a vector of coefficients for $X_i$, which is a matrix of individual, household, and geographic factors, and $D_{j(i)}$ is a vector of binary values for whether the observed 24-mo SPEI score indicated drought at a DHS site at the time the child health observation was made. The vector of drought conditions $D_{j(i)}$ at each DHS site interacts with a matrix of geographic variables, $G_{j(i)}$, which are in turn moderated by a vector of coefficients $\gamma$.

Because the geographic variables included in the regression explained much of the DHS site-level variation in nutrition outcomes, we avoided including terms that are typically used in multinational DHS analyses, such as a term for the interview year, a term for whether the site was urban or rural, as well as varying intercepts at the country or survey level (9). This allowed the spatiotemporal variation in HAZ scores to be explained by only the geographic variables included in the regression. We estimated our model using Least Absolute Shrinkage and Selection Operator (LASSO) regularization, which is particularly apt for cases like this one, where regression is being used with a large number of covariates to make predictions (53). Using the LASSO, redundant covariates will drop out of the model. To better fit the model and facilitate comparison between the coefficients of the covariates, we first log-transformed some variables and then scaled all variables from 0 to 1.

**Mapping Vulnerability.** We use the coefficients $\gamma$ from our model to predict where HAZ scores would be expected to decrease in the event of a drought, as well as the degree to which they would decrease. Because the individual- and household-level covariates $\beta$ were not modeled as interacting with the drought variables $D_{j(i)}$, we only need data on geographic factors to estimate changes in HAZ related to drought. Just as we excluded children from areas with greater than 20% built-up land cover or 95% bare land cover from our nutrition dataset, we excluded these areas from our maps.

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